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Reducing Energy Use Without Affecting Economic Objectives: A Sectoral Analysis

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Energy use has become an important issue when assessing the productivity of nations. In particular, it can give rise to greenhouse gas emissions, which are generally seen as an undesirable side-effect of economic growth. In this chapter, we conduct a macro-efficiency analysis of European countries that explicitly accounts for these undesirable side-effects of energy use. We present an efficiency-assessment method that is specially tailored for addressing this issue. A distinguishing feature of our efficiency analysis is that it concentrates on the sector level (agriculture, transport, and other industry) rather than the aggregate country level, which allows us to formulate more refined policy advice than would otherwise be possible.[42]

Undesirable outputs and input efficiency

Our analysis models the production behaviour of a particular economic sector as using two inputs (capital and energy) to pursue two main economic objectives – economic growth (measured as added value) and job creation (measured by the employment rate) – under the restriction that greenhouse gas emissions should be kept as low as possible. We explicitly model greenhouse gases as undesirable by-products of the production process. Formally, this means that European sectors use two inputs (capital and energy) to produce two good outputs (added value and employment) and one bad output (equivalent CO_2 emissions).[43]

The specific focus of our efficiency analysis is on the input side of the production process. Our method of measuring efficiency quantifies the maximum input reduction for a given level of output. This can provide useful policy data in

42 Other industry stands for construction, manufacturing, electricity, gas and water.

43 Equivalent CO2 emissions is an aggregate measure of greenhouse gas emissions; see the section on data for more details.

at least two ways. First, our efficiency results provide information on profitable input allocations: they tell countries to what extent a given sector can reduce its inputs, information that can then be used (more) productively in a different sector. Second, (fossil) energy use and, to a somewhat lesser extent, capital use is often directly linked with the emission of CO_2. As such, identifying an inefficient (over)use of energy or capital can directly suggest possibilities for reducing pollution (CO_2) while preserving the given level of the other good outputs.

A tailored efficiency model

A very popular method for analysing the productive behaviour of decision-making units (DMUs) such as countries, sectors, and firms is data envelopment analysis (DEA), which was originally introduced by Charnes et al. (1978). Essentially, this method benchmarks DMUs by measuring their input-output performance relative to other (observed) DMUs that operate in a similar production environment.[44] We see two main reasons for the widespread popularity of DEA. First, it is easily implemented. The computation of DEA efficiency measures merely requires solving simple linear programming problems. Second, DEA is intrinsically non-parametric. It does not require any prior (and typically non-verifiable) parametric assumptions about the functional relationship between inputs and outputs (that is, about the production technology). As such, it provides the greatest possible assurance that functional misspecification will not contaminate the efficiency analysis.

As indicated above, we compute the maximum input reduction for a given level of output. In this respect, we make use of a tailored DEA model that is designed for dealing with bad inputs. In particular, we build on original work of Cherchye *et al*. (2012) and Cherchye *et al*. (2013) to design an efficiency-measurement methodology that models the production of each (bad and good) output in terms of a *separate* output-specific production technology, while at the same time allowing for interdependencies between production processes through inputs that contribute *simultaneously* to multiple outputs. In other words, we explicitly account for the simultaneous production of different (good and bad) outputs through *joint* inputs while avoiding the requirement for specific (often non-verifiable) technology assumptions to model the production of bad outputs. As extensively discussed in Cherchye *et al*. (2012) and Cherchye *et al*. (2013), this approach significantly increases the discriminatory power of the efficiency analysis without making extra (non-verifiable) assumptions and, importantly, it also accounts naturally for the fact that it is usually impossible to produce good outputs without generating some bad output.

44 See, for example, Färe et al. (1994a), Cooper *et al.* (2007), Fried *et al.* (2008), and Cook and Seiford (2009) for extensive reviews of DEA.

Related literature

We can distinguish two different approaches to incorporating bad outputs in 'traditional' DEA.[45] The first approach consists of using standard efficiency models and translating the undesirable (bad) outputs into desirable (good) outputs through an appropriate transformation. Scheel (2001) points out three ways to do this: (i) take the additive inverse of bad outputs (multiply by −1, following Koopmans (1951)); (ii) take the multiplicative inverse of the bad outputs (following Golany and Roll (1989)); (iii) or incorporate bad outputs as inputs. The second approach consists of using the concept of a so-called 'environmental' DEA technology, which requires making the (usually non-verifiable) technological assumptions of weak disposability (reducing bad output requires a proportional reduction of the good output) and null-jointness (zero bad output requires zero good output). Färe and Grosskopf (2004) provide a detailed discussion of this last approach. As we explain in the section on methodology, we adopt the first approach in exposition and so avoid extra technological assumptions. In particular, we explicitly consider CO_2 emission as an output of the production process, and we use joint inputs to model the interdependency between this output and the other outputs.

At this point, it is also worth mentioning that the literature on efficiency measurement has already devoted considerable attention to the question of whether and to what extent countries act efficiently in producing GDP and creating jobs while minimising undesirable greenhouse gases (see, for example, Ramanathan (2006), Zhou *et al*. (2008), and Lozano and Gutierrez (2008) for surveys). Most of this existing work used one of the two approaches described above and focused on the country level. A main conclusion of these earlier studies is that ignoring CO_2 emissions (as negative externalities of the production process) may lead to severely biased efficiency results. All this provides a direct motivation for our own empirical analysis, which focuses on a sectoral efficiency analysis while taking CO_2 emissions into account.

Our main contributions

Summarising, our study contributes to the existing literature in two ways. First, we apply a tailored method to deal with bad (environmental) outputs in DEA evaluations of productive efficiency. We believe that modeling bad and good outputs as being associated with different (interdependent) technologies yields a more realistic modeling of the production environment.

Second, we do not consider the aggregate country efficiency, but rather measure efficiency at the sectoral level (Agriculture, Transport and Industry). In our opinion, a sector-level analysis leads to more balanced (i.e., sector-specific) policy recommendations. In particular, our empirical application considers the sectoral performance of 18 European countries from 2000 to 2007. We use the added value per capita and employment rate as 'good' outputs, and the equivalent

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45 See Zhou *et al*. (2008) for a survey.

CO_2 emissions per capita as a 'bad' output.[46] Our inputs are capital and energy consumption per capita.[47]

Outline
The remainder of this chapter is organised as follows. The first section presents our methodology for efficiency measurement, the second introduces our data, the third presents our empirical application, and the last section draws conclusions.

Methodology

As indicated above, we consider a DEA method that assesses input minimisation for a given level of output. In this section, we build on original work of Cherchye et al. (2012) and Cherchye *et al*. (2013) to present a method that is specially tailored for dealing with both good and bad outputs. The section is structured as follows. The first subsection introduces our notation and terminology. The second defines our measure of technical efficiency. The third shows how our framework can be used for dynamic efficiency analysis that focuses on intertemporal efficiency trends.

Preliminaries

We start by introducing our notations and the concept of input requirement sets. Using a different input requirement set for every individual output (good or bad) explicitly recognises that each output is characterised by its own production technology.

Inputs and outputs
We assume a production technology that uses N inputs, captured by the vector $\boldsymbol{X}$, for producing M outputs, captured by the vector $\boldsymbol{Y}$. As we will explain below, the output vector $\boldsymbol{Y}$ can contain both good outputs (those related to GDP and job creation) and bad outputs (related to CO_2 emissions).

The inputs (capital and energy) can be characterised as *joint* since they are used to produce all outputs simultaneously.[48] These joint inputs obtain interdependence between the different outputs that are produced. Actually, this interdependence is directly relevant for our own application to good and bad outputs: it indeed seems to be impossible to produce good outputs without producing the bad output.

Formally, we represent good outputs by the vector $\boldsymbol{Y}^G \in \mathbb{R}_+^{M_{good}}$, which thus contains the desirable outcomes of the production process, and bad outputs

46 The added value is often used as a proxy for GDP when the DMUs are sectors or states; see, for example, Färe *et al*. (2001).

47 We use per capita figures for inputs and outputs to correct for scale differences across countries.

48 At this point, we indicate that our methodology can actually be extended to deal with inputs that are not joint but specific to individual outputs. We will abstract from such an extension in what follows. See Cherchye *et al*. (2012) for dealing with output-specific inputs in a setting similar to ours.

by the vector $\boldsymbol{Y}^B \in \mathbb{R}_+^{M_{bad}}$, which captures the undesirable by-products of the production process. By construction, we obtain that $M_{good} + M_{bad} = M$. As indicated in the introduction, the application that follows will use added value and the employment rate as the good outputs and equivalent CO_2 emissions as the bad output, which yields $M_{good} = 2$ and $M_{bad} = 1$.

To operationalise our approach, we must integrate the undesirable feature of bad outputs in our construction of the output vector $\boldsymbol{Y}$. This requires converting bad outputs into good outputs. Referring to our discussion in the introduction, such a conversion may be achieved, for example, by multiplying the bad output by –1 or by taking the reciprocal of the bad output values. In general, we can represent the transformation of the bad outputs by the function $g(\boldsymbol{Y}^B)$. Our two examples then comply with $g(\boldsymbol{Y}^B) = -\boldsymbol{Y}^B$ or $g(\boldsymbol{Y}^B) = 1/\boldsymbol{Y}^B$. For a given specification of the function $g(\boldsymbol{Y}^B)$, we obtain the output vector $\boldsymbol{Y}$ as:

$$\boldsymbol{Y} = \left(y^1, \ldots, y^M\right)' = \begin{bmatrix} \boldsymbol{Y}^G \\ g\left(\boldsymbol{Y}^B\right) \end{bmatrix}$$

At this point, it is important to note that the value of our efficiency measure (introduced in the next section) will be the same for the two specifications of $g(\boldsymbol{Y}^B)$ that we presented above (namely, multiplication or taking reciprocals), which we see as an attractive feature of our method. See Cherchye *et al.* (2013) for a more detailed discussion.

Input requirement sets

It follows from our discussion above that we assume all outputs $\boldsymbol{Y}$ to be produced simultaneously by the inputs $\boldsymbol{X}$. When using y^m to represent the mth ($m = 1, \ldots, M$) output, we then associate a production technology with each individual y^m, which describes the relation between the joint inputs $\boldsymbol{X}$ and the output y^m. In terms of our application, this defines separate production technologies for the outputs of added value, employment rate, and CO_2 emissions. Importantly, these technologies are interdependent because of the joint inputs.

Formally, the technology of each output m is represented by input requirement sets $I^m(y^m)$, which contain all the combinations of the joint inputs $\boldsymbol{X}$ that can produce the output quantity y^m:

$$I^m(y^m) = \{\boldsymbol{X} \in \mathbb{R}_+^N | (\boldsymbol{X}, y^m) \in T^m\}$$

where $T^m = \{(\boldsymbol{X}, y^m) \in \mathbb{R}_+^{N+M} | \boldsymbol{X} \textit{ can produce } y^m\}$ is the production technology set containing the feasible combinations of input quantities $\boldsymbol{X}$ and output quantities y^m. By explicitly describing this production technology in terms of output-specific input requirement sets, we obtain a more precise modeling of the interaction between inputs and outputs. As formally discussed in Cherchye *et al.* (2012), this approach significantly enhances the discriminatory power of the efficiency analysis without making extra (non-verifiable) assumptions.

Technical efficiency measurement

In what follows, we will first define our technical efficiency measure for some given input requirement sets $I^m(y_t^m)$. In practice, however, because we typically do not observe the 'theoretical' sets $I^m(y_t^m)$ we need to use empirical approximations $\hat{I}^m(y_t^m)$. To obtain these empirical sets, we follow the usual DEA practice and construct $\hat{I}^m(y_t^m)$ on the basis of some maintained technology axioms. Using the resulting empirical input sets then allows us to compute our technical input efficiency measure in practical applications.

Defining technical input efficiency

In practice, technical efficiency measurement starts from an observed set of input and output data associated with a sample of DMUs. For each DMU $t = 1, \dots T$ (in our case production sectors of European countries), we observe the inputs $\boldsymbol{X}_t$ and the (good and bad) outputs $\boldsymbol{Y}_t$ (with y_t^m the quantity of output m). Taken together, this gives the dataset S:

$$S = \{(\boldsymbol{X}_t, \boldsymbol{Y}_t) | t = 1, \dots, T\}$$

Following our previous discussion, for some given set S we can define the input sets $I^m(y_t^m)$ which contain all the input combinations that can produce the output quantities y_t^m. These input sets are bounded from below by the input isoquants $IsoqI^m(y_t^m)$ which are defined as:

$$IsoqI^m(y_t^m) = \{\boldsymbol{X} \in I^m(y_t^m) | for\ \beta < 1, \beta\boldsymbol{X} \notin I^m(y_t^m)\}$$

Intuitively, $(\boldsymbol{X}, y_t^m) \in IsoqI^m(y_t^m)$ means that the inputs $\boldsymbol{X}$ can be thought of as 'minimal' input quantities to produce the output quantity y_t^m; it is impossible to further reduce these inputs (equiproportionately) for the given output. We say that $IsoqI^m(y_t^m)$ represents the 'technically efficient frontier' of the set $I^m(y_t^m)$.

Given that the set $IsoqI^m(y_t^m)$ contains all technically efficient input quantities, it is natural to quantify technical efficiency of some evaluated input combination in terms of the distance to this isoquant. A popular distance measure is the radial input distance function $D_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ that was originally proposed by Shephard (1970). This distance function measures the maximum equiproportionate reduction of all inputs $\boldsymbol{X}_t$ for a given output production $\boldsymbol{Y}_t$. Formally, $D_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ is defined as:

$$D_t(\boldsymbol{Y}_t, \boldsymbol{X}_t) = max\left\{\phi \middle| \forall \text{m}: \left(\frac{\boldsymbol{X}_t}{\phi}\right) \in I^m\left(y_t^m\right)\right\}$$

We can verify that $D_t(\boldsymbol{Y}_t, \boldsymbol{X}_t) \geq 1$ if, for all m, $\boldsymbol{X}_t \in I^m(y_t^m)$. Next, $D_t(\boldsymbol{Y}_t, \boldsymbol{X}_t) = 1$ indicates that, for some m, $\boldsymbol{X}_t \in IsoqI^m(y_t^m)$ and thus, given our above discussion, technically efficient production.

In what follows, we will take the reciprocal of the function $D_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ as our measure of technical efficiency:

$$TE_t(\boldsymbol{Y}_t,\boldsymbol{X}_t) = \frac{1}{D_t(\boldsymbol{Y}_t,\boldsymbol{X}_t)} = min\{\theta \mid \forall m: (\theta \boldsymbol{X}_t) \in I^m(y_t^m)\}$$

This measure is known as the Debreu-Farrell measure of technical efficiency. It has a natural interpretation as indicating the degree of efficiency; it is situated between 0 and 1, with higher values indicating better performance (i.e., less technical inefficiency). More specifically, $TE_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ defines the maximal equiproportionate input reduction (captured by $\theta\boldsymbol{X}_t$) that still allows the DMU to produce the output $\boldsymbol{Y}_t$. This Debreu-Farrell input-efficiency measure is the most commonly used efficiency measure in the DEA literature. We have tailored it to our specific multi-output setting by defining it in terms of output-specific input sets $I^m(y_t^m)$.

Technology axioms

The input efficiency measure $TE_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ that we defined above is not directly useful in practice. It is defined in terms of the 'theoretical' sets $I^m(y_t^m)$, which are typically not observed. In what follows, we will build an empirical approximation $\hat{I}^m(y_t^m)$ of any input set $I^m(y_t^m)$.

As is standard in DEA, we proceed axiomatically. In particular, we start from four axioms regarding the production technology. We assume that the input requirement sets are nested (Axiom 1), monotone (Axiom 2), and convex (Axiom 3). We also assume that what we observe is feasible (Axiom 4).[49] Then, any empirical set $\hat{I}^m(y_t^m)$ satisfies the 'minimum extrapolation principle', which means that it is the smallest approximation of $I^m(y_t^m)$ that effectively satisfies the four stated axioms. This minimum extrapolation principle guarantees that $\hat{I}^m(y_t^m) \subseteq I^m(y_t^m)$ – that is, the empirical set $\hat{I}^m(y_t^m)$ provides an inner bound approximation of the true (but unobserved) set $I^m(y_t^m)$.

Axiom 1 (nested input sets): $y^m \geq y^{m'} \Rightarrow I^m(y^m) \subseteq I^m(y^{m'})$.

In words, Axiom 1 says that, if some input $\boldsymbol{X}$ can produce the output y^m, then it can also produce less output (i.e., $y^{m'}$). Essentially, this means that outputs are freely disposable.

Axiom 2 (monotone input sets): $\boldsymbol{X} \in I^m(y^m)$ and $\boldsymbol{X}' \geq \boldsymbol{X} \Rightarrow \boldsymbol{X}' \in I^m(y^m)$.

Axiom 2 complements Axiom 1 and states that inputs are freely disposable – that is, more input never leads to less output. Again, this is often a very reasonable assumption to make.

49 See, for example, Varian (1984), Tulkens (1993), Petersen (1990), Bogetoft (1996), and Cherchye *et al.* (2012) for discussions of these technology assumptions in a (DEA) production context similar to ours.

Axiom 3 (convex in put sets): $\boldsymbol{X} \in I^m(y^m)$ and $\boldsymbol{X}' \in I^m(y^m) \Rightarrow \forall\lambda \in [0,1]: \lambda\boldsymbol{X} + (1-\lambda)\boldsymbol{X}' \in I^m(y^m)$.

Axiom 3 says that, if two input combinations $\boldsymbol{X}$ and $\boldsymbol{X}'$ can produce the output y^m, then any convex combination of these inputs can also produce the same output. Intuitively, it imposes that marginal rates of input substitution are nowhere decreasing when moving along the isoquant of the set $I^m(y^m)$.

Axiom 4 (observability means feasibility): $(\boldsymbol{X}_t, \boldsymbol{Y}_t) \in S \Rightarrow \forall$m: $\boldsymbol{X}_t \in I^m(y_t^m)$.

Axiom 4 states that what we observe is certainly feasible. Or, if we observe $\boldsymbol{X}_t$ in combination with $\boldsymbol{Y}_t$, then we conclude that $\boldsymbol{X}_t$ can effectively produce $\boldsymbol{Y}_t$. Basically, this axiom guarantees that our empirical input requirement sets $\hat{I}^m(y_t^m)$ will effectively be based on the observed input-output combinations contained in the dataset S.[50]

Using the minimum extrapolation principle, we define the empirical input sets $\hat{I}^m(y_t^m)$ as the smallest input sets that are consistent with the Axioms 1–4. We can verify that, for any output y_t^m, these sets are defined as:[51]

$$\hat{I}^m\left(y_t^m\right)=\left(\boldsymbol{X}\;\middle|\;\begin{array}{l}\forall\text{m: }\sum_s \lambda_s^m \boldsymbol{X}_s \leq \boldsymbol{X} \text{ with } \sum_s \lambda_s^m = 1\ ,\\ \lambda_s^m \geq 0 \text{ and for all s: } \mathrm{y}_s^m \geq y_t^m\end{array}\right)$$

Measuring technical input efficiency

Using our approximations $\hat{I}^m(y_t^m)$ of the sets $I^m(y_t^m)$, we can now define an empirical counterpart of the input efficiency measure $TE_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$. Specifically, our following application will use the empirical measure:

$$\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t) = min\{\theta | \forall\text{m: } (\theta\boldsymbol{X}_t) \in \hat{I}^m(y_t^m)\}$$

As before, we have that $\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ is situated between 0 and 1, with lower values indicating greater technical inefficiency. Because $\hat{I}^m(y_t^m) \subseteq I^m(y_t^m)$, we also have that $\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t) \geq TE_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$. In words, $\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ provides a 'favourable' estimate of the theoretical measure $TE_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$. Intuitively, by taking the best possible efficiency score, this favourable estimate gives the benefit of the doubt to the DMUs under evaluation in the absence of complete technology information.

Interestingly, using our above definition of $\hat{I}^m(y_t^m)$, we can compute $\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ through simple linear programming. In particular, it suffices to solve the programme:

50 We note that Axiom 4 actually assumes that all input and output data are measured accurately. We will return to the possibility of extending our methodology to deal with measurement error in the beginning of the section on efficiency analysis.

51 See Cherchye *et al*. (2012) for a formal proof.

$$\widehat{TE}_t(\mathbf{Y}_t,\mathbf{X}_t)=\min_{\lambda_s^m(m\in\{1,\ldots,M\},s\in\{1,\ldots,T\})}\theta$$

s.t.

(1) $\forall$m: $\sum_s \lambda_s^m \boldsymbol{X}_s \leq \theta \boldsymbol{X}_t$ for all s: $y_s^m \geq y_t^m$

(2) $\forall$m: $\sum_s \lambda_s^m = 1$ for all s: $y_s^m \geq y_t^m$

(3) $\forall$m: $\forall$s: $y_s^m \geq 0$

(4) $\theta \geq 0$

As a final remark, we indicate that the technical efficiency measure $\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ also has an interesting interpretation as a measure of multioutput cost efficiency. In particular, Cherchye *et al.* (2012) demonstrate that the dual version of the above linear programming problem represents our technical efficiency measure as the ratio of minimal over actual cost defined at shadow prices. These authors argue that this allows for multi-output cost-efficiency analysis that naturally extends the single-output cost-efficiency analysis originally considered by Afriat (1972), Hanoch and Rothschild (1972), Diewert and Parkan (1983), and Varian (1984). See Cherchye *et al*. (2008) for more details on this cost-efficiency perspective.

Dynamic efficiency measurement

In our application, we will use the methodology introduced above for assessing the technical efficiency of DMUs (in our case production sectors of countries) at a given point of time (a particular year), which effectively boils down to static efficiency measurement. In our application, we use a panel dataset, which means that we observe the same DMUs in multiple consecutive time periods. Interestingly, this panel data structure allows us to conduct a dynamic efficiency evaluation.

Specifically, in our case we will evaluate dynamic efficiency in terms of technical efficiency changes over time. To introduce our dynamic efficiency measure, we need to introduce some additional notation, which relates to the panel structure of our dataset. Specifically, let us consider a setting with observations on T DMUs for K periods. We now have a dataset S^k for each period k:

$$S^k = \{(\boldsymbol{X}_t^k, \boldsymbol{Y}_t^k) \mid t = 1, \ldots, T\}$$

On the basis of each such dataset, we can use our above methodology to define a technical efficiency measure $\widehat{TE}_t^k(\boldsymbol{X}_t^k, \boldsymbol{Y}_t^k)$ for each DMU t and period k. Essentially, this measure evaluates the static efficiency of DMU t by comparing its input-output performance to those of all other DMUs observed in the same period. Using this, we can define, for each DMU t, the following measure of efficiency change between periods k and $k+1$:

$$\textit{Efficiency Change} = \widehat{CE}_t^{k+1} = \frac{\widehat{TE}_t^{k+1}\left(\boldsymbol{X}_t^{k+1}, \boldsymbol{Y}_t^{k+1}\right)}{\widehat{TE}_t^{k}\left(\boldsymbol{X}_t^{k}, \boldsymbol{Y}_t^{k}\right)}$$

The interpretation is immediate: if $\widehat{CE}_t^{k+1} > 1$ then the technical efficiency of DMU t has improved between periods k and $k+1$, while the opposite conclusion holds if $\widehat{CE}_t^{k+1} < 1$. In our case, improved (or deteriorated) technical efficiency signals a better (or worse) allocation of inputs in period $k+1$ than in period k (accounting for the possibly different output quantities produced in the two periods). Clearly, this reveals interesting information from the perspective of policy evaluation, which is particularly relevant for our following application

As a concluding remark, it is interesting to relate our efficiency change measure to the literature on dynamic DEA. See, for example, Färe and Grosskopf (1992), Kumar and Russell (2002), and Henderson and Russell (2005). Based on the original work of Caves *et al.* (1978), these authors set out a DEA-based framework for disentangling changes in total productivity (i.e., changes in the ratio of aggregate output over aggregate input) according to alternative sources of productivity change. In this framework, our efficiency measure $\widehat{CE}_t^{k+1}$ is a so-called catch-up indicator, which quantifies the degree to which a particular DMU catches up with (or, conversely, falls behind) the best-practice DMUs in period $k+1$ (as compared with period k).

From this perspective, it may actually be fruitful to extend our methodology to include the other components of productivity change included in the above mentioned framework. A particularly useful extension here pertains to the possibility of quantifying technology change (as a component of productivity change), which in the setting of our application can also be interpreted as 'change in the (policy) environment'. Specifically, this indicator of environmental change captures the extent to which, between any two periods k and $k+1$, the environment of the DMU under evaluation has become more or less favourable for achieving particular economic objectives (i.e., for creating added value and employment while reducing the emissions of greenhouse gases).[52] Clearly, such a measure may reveal interesting policy information, especially for the type of questions (related to European countries) that we address in this chapter. For the sake of compactness, however, we will not explore this further in what follows. But we do see this as a potentially interesting avenue for follow-up research.

52 Technically, the more or less favorable nature of the environment is then quantified by comparing the performances of the (reference) best practice DMUs in periods k and $k+1$. See Cherchye *et al.* (2007) for a detailed discussion of the interpretation of 'technology change' indicators in terms of changes in the policy environment in a European context comparable to ours.

Data

As indicated in the introduction to this chapter, we focus on three sectors (agriculture, transport, and other industry) of 18 European countries (EU-18), which we evaluate over the period 2000–07. The countries are Austria, Belgium, the Czech Republic, Denmark, France, Finland, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Slovakia, Slovenia, Spain, and Sweden. Aggregated over all countries, the three sectors represent 28% of total production (GDP), 35% of total employment, and 40% of total CO_2 emissions for the period under consideration (Table 4.1).

Table 4.1 *Size of the sectors, 2000–07 (%)*

	Agriculture	Transport	Industries	Total
GDP	2	6	20	28
Employment	4	6	25	35
CO_2 emissions	10	18	12	40

For each sector and every country, we consider three outputs and two inputs. Our good outputs are added value per capita and the employment rate, the bad output is CO_2 emissions per capita. Our inputs are capital per capita and energy per capita. We use per capita normalisations to account for scale differences across countries. Our data on CO_2 emissions and energy consumption come from the Eurostat database, while our data on capital, employment and added value are taken from the OECD database.

In what follows, we will highlight some sector characteristics through a descriptive analysis. In particular, we present trendlines depicting the evolution of each input and output dimension at the sample (EU-18) level. The Appendix reports additional details on our data.

Outputs

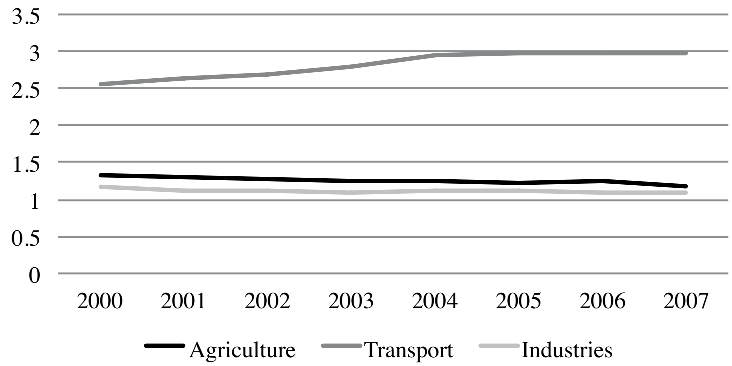
In this section, we present our three outputs. First, we consider the bad output, CO_2 emissions. We then turn to the good outputs of added value and employment.

The bad output: CO_2 emissions

The measure for CO_2 emissions is expressed in equivalent tonnes per capita and is an aggregate measure of greenhouse gas emissions such as CO_2, SO_x, and NO_x. The respective greenhouse gases are weighted by their global-warming potential. Figure 4.1 presents the trendlines for our three sectors, taking averages over the countries.

Figure 4.1 *CO_2 emissions in the EU-18*

Equivalent tonnes per capita



The trendlines for agriculture and industry are more or less the same and decrease only slowly during our sample period. On average, the agriculture sector produced 1.34 equivalent tonnes per capita in 2000 and 1.18 in 2007, while the industry sector generated 1.16 equivalent tonnes per capita in 2000 and 1.09 in 2007. For the transport sector, we observe a clearly different pattern. CO_2 emissions are much higher when compared to the other two sectors and, in addition, the trendline is increasing. On average, the greenhouse gas emissions for transport amount to no less than 2.56 tonnes per capita in 2000 and 2.97 in 2007.

Importantly, from Tables 4A.5 and 4A.6 in the Appendix we conclude that one should not focus solely on these average emissions. For our sample of observations, we find a great deal of heterogeneity in CO_2 emissions both across sectors and across countries. For instance, some countries exhibit increasing CO_2 emissions in the three sectors (e.g., Luxembourg and Ireland), while others have decreasing CO_2 emissions in two of the three sectors (e.g., Germany and Czech Republic). Not one country shows decreasing CO_2 emissions in all three sectors.

The good outputs: added value and employment

Our measure for the employment rate is given in full-time-equivalent workers as a percentage of the active population. Our proxy for GDP is gross added value (GAV) expressed in euros per capita. GAV is a measure of the value of goods and services produced in a particular sector of the economy. It is defined as the difference between outputs and intermediate inputs. Figures 4.2 and 4.3 depict the associated trendlines for the three sectors under study, where we again take averages over our 18 countries.

Figure 4.2 *Employment in the EU-18*

Workers per active population

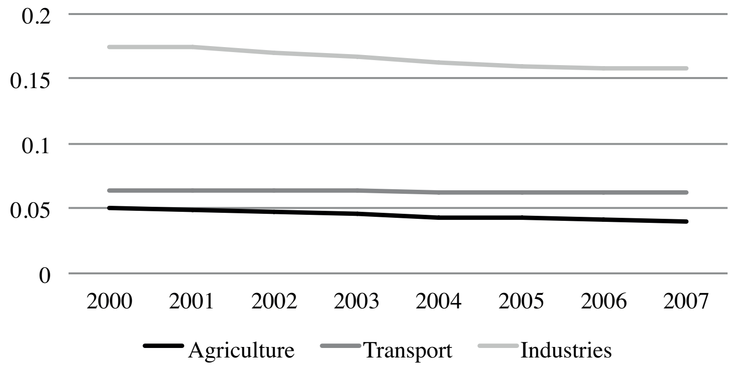
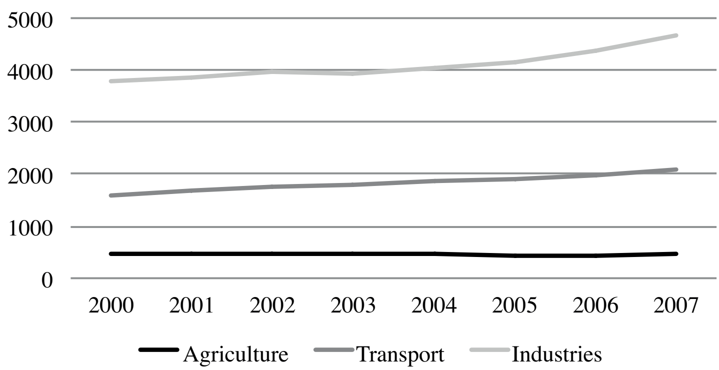


Figure 4.3 *Added value in the EU-18*

Euros per capita



Just as for CO_2 emissions, we again conclude that it is important to conduct a sector-level analysis. Industry is clearly dominating the other two sectors in the good outputs, while transport is slightly ahead of agriculture. Actually, these findings should not come as a big surprise given the numbers we reported in Table 4.1. However, the trendlines suggest that the pattern of evolution over time is quite different for the three sectors. In terms of the employment rate, industry and agriculture show a decreasing pattern, whereas transport remains more or less constant. With respect to added value, we find that the trendline is more or less stable for agriculture, while sharply increasing for the other two sectors.

Finally, Tables 4A.7–4A.10 in the Appendix confirm our earlier point on cross-observational heterogeneity. Specifically, even though most countries exhibit patterns that are fairly similar to the average patterns described above, we do observe a lot of variation over countries, sectors, and time.

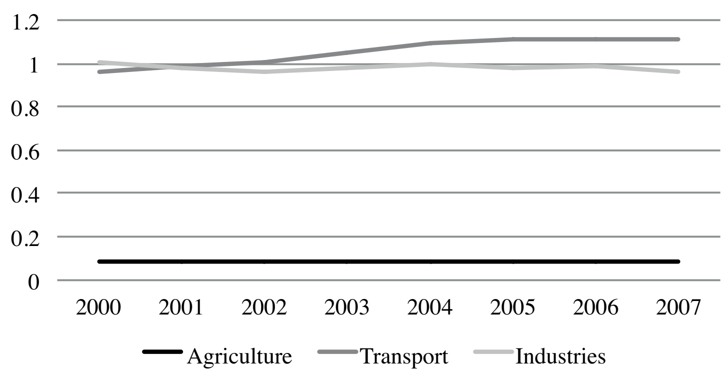
Inputs

In this section we present our two inputs. We will first consider energy and then focus on capital.

Energy
We use final energy consumption in tonnes of oil equivalent (toe) per capita.[53] Final energy consumption in industry includes consumption in all industrial sectors with the exception of the energy sector. Final energy consumption in transport covers consumption in all types of transportation (rail, road, air transport, and inland navigation). Figure 4.4 presents the corresponding trendlines for our sample.

Figure 4.4 *Energy in the EU-18*

Tonnes of oil equivalent per capita



As one may have expected, the transport sector is the biggest energy consumer (1.05 toe on average), and its energy consumption is increasing over time (0.99 toe on average in 2000 and 1.14 in 2007). In fact, the average energy consumption of the industry sector (0.98 toe) is quite similar to that of the transport sector, but the trendline is clearly different. Specifically, the energy consumption in industry is slowly decreasing from (on average) 1.00 toe in 2000 to 0.96 in 2007. Finally, the pattern of energy consumption of the agriculture sector is totally different. Compared with the other two sectors, this sector appears not very energy intensive (0.09 toe on average). In addition, its consumption of energy is more or less stable over time.

From Tables 4A.11 and 4A.12 in the Appendix we again conclude that these average figures hide a lot of heterogeneity in sectors and countries. For instance, we find quite different values for the standard deviations associated with the three sectors. In our opinion, this suggests that patterns of energy consumption

53 One toe = 1.07 x 10 cal (thermochemical) = 44.769 GJ = 42.46 MBtu (thermochemical).

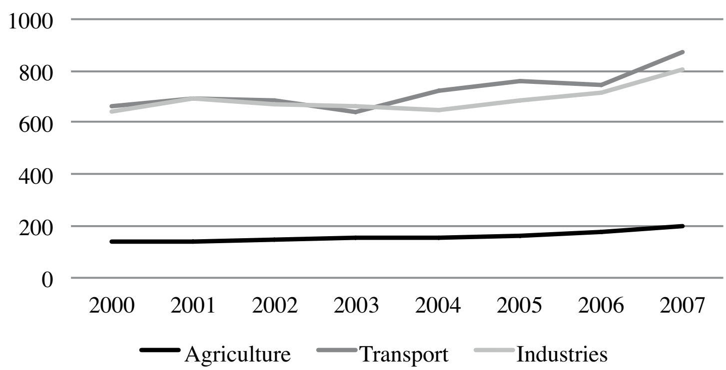
are not only sector-specific, but also country-specific. As argued before, our efficiency analysis will account for this feature.

Capital

We use gross fixed capital formation (expressed in euros per capita) as an indicator for the capital input. At this point, it is worth indicating that other studies have focused on more specific capital indicators (such as tractors, lands, human capital, and so on). For our study, however, we opt for gross fixed capital formation to enhance comparability over the three sectors. Figure 4.5 presents trendlines for our capital input.

Figure 4.5 *Capital in the EU-18*

Euros per capita



Just as for the energy input, we conclude that industry and transport are very comparable in terms of average values. In this case, too, the trendlines depict the same (increasing) pattern. As before, the agriculture sector uses much less of the capital input than the other two sectors and, although its capital use is increasing over time, the increase is also much more modest. Finally, and consistent with our earlier findings, Tables 4A.13 and 4A.14 in the Appendix plead once more for a country-specific and sector-specific analysis.

What do we learn from all this?

The patterns described above strongly indicate that the production of outputs and the use of inputs is country-specific and sector-specific. Similarly, the evolution of output and input over time also varies significantly by sector and country. These are important observations for the policymaker who wants to set objectives in terms of CO_2 production or energy use. For instance, our findings suggest that one should better specify sector-specific and country-specific objectives to reach the Europe 2020 objectives (stated in the EU's growth strategy for the coming decade).

This being said, the numbers that we have discussed above are only one side of the story. For instance, although transport is much more energy intensive than agriculture, it could well be that agriculture is not as efficient as transport in its use of energy. That is, the agriculture sector may well have more potential to reduce its energy consumption.

This is what we will investigate in the following (non-parametric) efficiency analysis. In particular, we will compare the performance of a given sector in one European country to the performance of that same sector in other countries. For the country under evaluation, this will identify whether and to what extent sector-specific efficiency gains are possible (meaning that less input can be used for the given output level). As explained before, a specific feature of our empirical analysis is that it simultaneously accounts for CO_2 emissions as an undesirable output.

Efficiency analysis

Using the data presented in the previous section, we next evaluate the productive efficiency of the three sectors under study for our sample of countries. In particular, for every sector and country we compute the input efficiency measure $\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ for each year of the time period 2000–07. This gives us information on the extent to which inputs have been allocated efficiently to achieve the three economic objectives that we focus on: reducing greenhouse gas emissions, creating jobs, and generating productivity growth. Attractively, the panel structure of our dataset also allows us to evaluate efficiency trends over time.

Before beginning our analysis, it is important to observe that sampling issues (e.g., measurement error and small-sample bias) may be a concern in the application at hand.[54] In turn, these problems may affect the reliability of the efficiency results that we report. In this respect, it is worth noting that the DEA literature has proposed alternative procedures to resolve sampling issues (see Daraio and Simar (2007) for a survey). For example, bootstrap (or subsampling) procedures can correct small-sample bias, and robust frontier procedures (such as order-*m* and order-α procedures) can improve the robustness of the efficiency scores with respect to outliers in the data. For compactness and to facilitate our discussion, we will not report results for these extended procedures here. However, we did apply alternative methods to check the extent to which our results were robust with respect to sampling issues. Our main qualitative conclusions proved quite robust.[55]

The remainder of this section unfolds as follows. The first subsection reports on the efficiency levels of the different sectors and countries under study. The second focuses on feasible input reductions that are revealed through our efficiency assessment. The third takes a dynamic viewpoint and looks at

54 The difference between the 'true' and estimated efficiency scores is called the bias. This bias can be greater with the smaller samples.

55 Detailed results of our robustness checks are available from the authors upon request.

efficiency trends over time. In particular, it considers whether we can discern specific catch-up patterns in the three sectors under evaluation.

Efficiency results

The results of our efficiency analysis are presented in Table 4.2. This table contains the average efficiency score (over the eight years in our sample) for each country and sector.

When considering the average scores per sector, we conclude that transport is clearly the most efficient sector. Again, this means that transport is the sector that uses its inputs most effectively to produce the given outputs. In particular, we find that the transport sector can reduce its inputs by no more than 4% (on average) for a fixed output. The possible input reductions for the agriculture and industry sectors are substantially more pronounced (14% and 12%, respectively). This confirms what we suggested before: although transport uses large amounts of input, there appears to be more potential for input reduction in the other two sectors.

Table 4.2 *Efficiency scores*

Country (DMU) *t*	Agriculture	Transport	Industries
Belgium	0.83	0.95	0.84
Czech Republic	0.95	0.97	0.83
Denmark	0.50	1	1
Germany	0.96	1	0.93
Ireland	1	0.76	1
Greece	1	1	1
Spain	1	0.85	0.92
France	0.99	1	1
Italy	0.96	1	0.77
Luxembourg	0.80	1	0.60
Hungary	0.89	1	1
Netherlands	0.62	0.99	1
Austria	0.80	0.90	0.88
Slovenia	0.93	0.90	0.83
Slovak Republic	1	1	0.82
Finland	0.89	1	0.90
Sweden	0.76	0.99	0.68
Norway	0.55	1	0.90
Average	*0.86*	*0.96*	*0.88*

Generally, we observe a great deal of heterogeneity in the efficiency scores across sectors and countries. This being so, it makes little sense, when focusing on a specific sector, to formulate objectives that do not take the identity of the country into account. Efficiency-enhancing strategies ought to be country-specific. For example, our results tell us that the Czech Republic should focus on industry to improve its overall efficiency level, while Ireland should concentrate on transport.

Possible energy reduction

To further illustrate our results in Table 4.2, we next quantify the possible energy reductions for every sector and country. This shows the extent to which countries can reduce their energy use in a given sector, without decreasing its output production. In fact, because (fossil) energy is directly linked with the production of CO_2 emissions, our results here also shed light on the degree to which CO_2 emissions can be decreased by behaving more efficiently.

As explained in the first section of the chapter, our input-oriented measure of technical efficiency $\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t)$ is defined as:

$$\widehat{TE}_t(\boldsymbol{Y}_t, \boldsymbol{X}_t) = min\{\theta | \forall \mathrm{m}: (\theta \boldsymbol{X}_t) \in \hat{I}^m(y_t^m)\}$$

and gives the maximal equiproportionate input reduction (captured by $\theta\boldsymbol{X}_t$) that still makes it possible to produce the given output ($\boldsymbol{Y}_t$). Based on this definition, for each DMU *t* we can define the relative and absolute input reductions as:

$$\widehat{IR}_t^R = Input\ Reduction\ (Relative) = (1 - \theta)$$

$$\widehat{IR}_t^A = Input\ Reduction\ (Absolute) = \boldsymbol{X}_t \times (1 - \theta)$$

Table 4.3 reports the feasible absolute energy reductions for our sample of countries. Between brackets we present the associated relative input reductions, which correspond to the efficiency scores given in Table 4.2. The results in Table 4.3 clearly demonstrate the value added of computing absolute input reductions corresponding to efficiency improvements and so further illustrate the usefulness of an efficiency analysis such as ours in arriving at effective policy recommendations. In our opinion, the absolute numbers in Table 4.3 are quite impressive. This is all the more true because, by construction, the input reductions given by our model define only the upper bounds on possible input savings of evaluated DMUs (i.e., the ‘benefit of the doubt’ interpretation of DEA measures that we indicated before).

Table 4.3 *Energy reduction (toe/persons)*

Country (DMU) *t*	Agriculture	Transport	Industries
Belgium	0.012 (17%)	0.045 (5%)	0.221 (16%)
Czech Republic	0.0026 (5%)	0.012 (3%)	0.162 (17%)
Denmark	0.082 (50%)	0	0
Germany	0.013 (4%)	0	0.052 (7%)
Ireland	0	0.278 (24%)	0
Greece	0	0	0
Spain	0	0.133 (15%)	0.0564 (8%)
France	0.002 (1%)	0	0
Italy	0.0024 (4%)	0	0.157 (23%)
Luxembourg	0.0107 (20%)	0	0.833 (40 %)
Hungary	0.0067 (11 %)	0	0
Netherlands	0.0963 (38%)	0.0015 (1%)	0
Austria	0.0141 (20%)	0.110 (10%)	0.119 (12%)
Slovenia	0.0023 (7%)	0.070 (10%)	0.136 (17%)
Slovak Republic	0	0	0.146 (18%)
Finland	0.0166 (11%)	0	0.245 (10%)
Sweden	0.0211 (24%)	0.012 (1%)	0.460 (32%)
Norway	0.0750 (45%)	0	0.139 (10%)
Average	*0.0191*	*0.0367*	*0.152*

Efficiency trends

While our results in Tables 4.2 and 4.3 already reveal interesting conclusions, they do not shed any light on efficiency trends. Specifically, they do not tell us whether or to what extent sectors and countries are behaving more efficiently over time. We conclude our empirical application by exploring these issues of dynamic efficiency.

To do so, we use the measure of efficiency change (or catch-up) that we defined previously, which we calculate as the ratio of efficiency scores corresponding to two consecutive periods of time. A value for this catch-up measure above (or below) unity then indicates an efficiency improvement (of deterioration) of the DMU under study between the two periods. Essentially, this means that the DMU allocates its inputs more (less) optimally in the second period than in the first period.

Table 4.4 presents our results on efficiency change for the three sectors under study. We find that, on average, the catch-up measure is about one in the transport sector, which suggests that, for this sector, the average efficiency score remained more or less constant over the period 2000–07. For agriculture, the measure of efficiency change is slightly more than one, suggesting that the average country is catching up in terms of its efficiency performance. The opposite is true of the industry sector.

All in all, these (average) numbers are fairly similar over sectors and seem to indicate that there is not much improvement in terms of efficient input use for the given outputs. However, we also observe from Table 4.4 that there is (often substantial) variation in sector-specific efficiency change over years. In this respect, it is also important to recall that catching-up effects represent only one part of dynamic efficiency. As we indicated in the section on measuring dynamic efficiency, it may be interesting to complement the efficiency-change measure that we consider here by a measure of technology-change effects on the observed sector productivity. We see the development of such a technology-change measure for our type of multi-output DEA analysis as a valuable avenue for follow-up research.

Table 4.4 *Catch-up effects*

	2001	2002	2003	2004	2005	2006	2007	Mean
Agriculture	1.01	0.96	0.98	1.09	0.99	0.97	1.05	1.01
Transport	0.98	1	1	1.01	0.99	0.99	1	1
Industry	0.93	1.05	0.88	1.10	1.04	0.99	0.93	0.99

Conclusion

Focusing on three sectors (agriculture, transport, and other industry) in 18 European countries, we have evaluated the efficient use of two inputs – energy and capital – to achieve two main economic goals: economic growth and job creation. A distinguishing feature of our analysis is that we explicitly account for the negative side-effects of energy use by including the reduction of greenhouse gas emissions as a third main economic objective. We represented the first two objectives as 'good' (desirable) outputs and the last as a 'bad' (undesirable) output.

Building on Cherchye et al. (2012) and Cherchye *et al.* (2013), we presented a specific DEA methodology that describes the production of each output (good or bad) as resulting from a separate technology, while at the same time accounting for interdependencies in the production processes through joint inputs. This effectively accounts for the fact that it is usually impossible to produce good outputs without generating the bad output. Moreover, our approach does not require specific (often non-verifiable) technology assumptions to model the production of bad outputs (such as weak disposability or null-jointness).

Our empirical application demonstrated the value-added of both our sector-level orientation and our efficiency-measurement methodology. In particular, our analysis allowed us to identify sector-specific efficiency levels, efficiency trends, and feasible energy reductions (removing not only input inefficiencies, but also greenhouse gas emissions). A most notable finding was that countries often exhibit quite different performance patterns depending on the sector that is evaluated. In our opinion, this directly suggests the usefulness of evaluating productive efficiency at the sector level (and not only at the aggregate country level). In this respect, our results can lead to sector-specific policy recommendations for every country.

References

Afriat, S. (1972), "Efficiency estimation of production functions", *International Economic Review* 13, pp. 568–98.

Bogetoft, P. (1996), "DEA on relaxed convexity assumptions", *Management Science* 42, pp. 457–65.

Caves, D. W., L. R. Christensen and W. E. Diewert (1978), "The economic theory of index numbers and the measurement of input, output, and productivity", *Econometrica* 50, pp. 1392–1414.

Charnes, A., W. W. Cooper and E. Rhodes (1978), "Measuring the efficiency of decision making units," *European Journal of Operational Research* 2, pp. 429–44.

Cherchye, L., B. De Rock, B. Dierynck, F. Roodhooft and J. Sabbe (2012), "Opening the black box of efficiency measurement: input allocation in multi-output settings", *Operations Research,* forthcoming

Cherchye, L., B. De Rock and F. Vermeulen (2008), "Analyzing cost-efficient production behavior under economies of scope: A nonparametric methodology", *Operations Research* 56, pp. 204–21.

Cherchye, L., B. De Rock and B. Walheer (2013), "Multi-output efficiency with good and bad outputs" ECARES Working Paper No. 2013-35, Université libre de Bruxelles.

Cherchye, L., K. Lovell, W. Moesen and T. Van Puyenbroeck (2007), "One market, one number? A composite indicator assessment of EU internal market dynamics", *European Economic Review* 51, pp. 749–79.

Cook, W. D. and L. M. Seiford (2009), "Data envelopment analysis (DEA)—Thirty years on", *European Journal of Operational Research* 192, pp. 1–17.

Cooper, W. W., L. M. Seiford and K. Tone (2007), *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*, 2nd Edition, Springer.

Daraio, C. and L. Simar (2007), *Advanced Robust and Nonparametric Method In Efficiency Analysis Methodology and Applications*, Springer.

Diewert, W. E. and C. Parkan. 1983. "Linear Programming Tests of Regularity Conditions for Production Frontiers", In *Quantitative Studies on Production and Prices*, ed. W. Eichhorn, R. Henn, K. Neumann, and R. W. Shephard. Würzburg and Vienna: Physica-Verlag.

Färe, R. and S. Grosskopf (1992), "Malmquist Productivity Indexes and Fisher Ideal Indexes", *Economic Journal* 102, pp. 158–60.

——— (2004), "Modeling undesirable factors in efficiency evaluation: comment", *European Journal of Operational Research* 157, pp. 242–45.

Färe, R., S. Grosskopf and C. A. K. Lovell (1994), *Production Frontiers*, Cambridge: Cambridge University Press.

Färe, R., S. Grosskopf, M. Norris and Z. Zhang (1994), "Productivity growth, technical progress, and efficiency change in industrialized countries", *American Economic Review* 84, pp. 66–83.

Färe, R., S. Grosskopf and C. Pasurka (2001), "Accounting for air pollution emissions in measures of state manufacturing productivity growth", *Journal of Regional Science* 41, pp. 381–409.

Fried, H., C. A. K. Lovell and S. Schmidt (2008), *The Measurement of Productive Efficiency and Productivity Change,* Oxford: Oxford University Press.

Golany, B. and Y. Roll (1989), "An application procedure for DEA", *Omega* 17, pp. 237–50.

Hanoch, G. and M. Rothschild (1972), "Testing assumptions of production theory: A nonparametric approach", *Journal of Political Economy* 80, pp. 256–75.

Henderson, D. and R. R. Russell (2005), "Human capital and convergence: A production-frontier approach", *International Economic Review* 46, pp. 1167–1205.

Koopmans, T. C. (1951), "Analysis of Production as an Efficient Combination of Activities", in T. C. Koopmans (ed.), *Activity Analysis of Production and Allocation: Proceedings of a Conference*, New York: John Wiley & Sons.

Kumar, S. and R. R. Russell (2002), "Technological change, technological catch-up, and capital deepening: Relative contribution to growth and convergence", *American Economic Review* 92, pp. 527–48.

Lozano, S. and E. Gutierrez (2008), "Non-parametric frontier approach to modeling the relationships among population, GDP, energy consumption and CO_2 emissions", *Ecological Economics* 66(4), pp. 687–99.

Petersen, N. C. (1990), "Data envelopment analysis on a relaxed set of assumptions", *Management Science* 36, pp. 305–14.

Ramanathan, R. (2006), "A multi-factor efficiency perspective to the relationships among world GDP, energy consumption and carbon dioxide emissions", *Technological Forecasting and Social Change* 73, pp. 483–94.

Scheel, H. (2001), "Undesirable outputs in efficiency valuations", *European Journal of Operational Research* 132, pp. 400–10.

Shephard, R. W. (1970), *Theory of Cost and Production Functions*, Princeton, NJ: Princeton University Press.

Tulkens, H. (1993), "On FDH analysis: Some methodological issues and applications to retail banking, courts and urban transit", *Journal of Productivity Analysis* 4, pp. 183–210.

Varian, H. R. (1984), "The non-parametric approach to production analysis", *Econometrica* 52, pp. 579–98.

Zhou, P., B. W. Ang and K. L. Poh (2008),"A survey of data envelopment analysis in energy and environmental studies", *European Journal of Operational Research* 189, pp. 1–18.

Appendix: Descriptive statistics

Table 4A.1 *CO_2 emissions for each year (tonnes per person)*

	2000	2001	2002	2003	2004	2005	2006	2007
Agriculture								
Mean	1.34	1,31	1.28	1.25	1.24	1.21	1.24	1.18
Max	5.20	4.99	4.86	4.80	4.68	4.54	4.88	4.11
Min	0.65	0.66	0.66	0.63	0.60	0.60	0.59	0.60
Std	1.03	0.98	0.95	0.94	0.91	0.89	0.96	0.79
Transport								
Mean	2.56	2.63	2.70	2.81	2.94	2.99	2.96	2.97
Max	10.96	11.51	12.16	13.30	15.00	15.25	14.63	13.85
Min	0.78	0.89	0.92	0.94	0.99	1.17	1.08	1.22
Std	2.18	2.29	2.43	2.68	3.06	3.11	2.97	2.78
Industries								
Mean	1.16	1.12	1.11	1.09	1.13	1.11	1.10	1.09
Max	2.58	2.45	2.28	2.13	2.27	2.18	2.15	2.12
Min	0.51	0.54	0.54	0.56	0.56	0.45	0.47	0.47
Std	0.53	0.50	0.49	0.47	0.51	0.49	0.49	0.49

Table 4A.2 *CO_2 emissions for each country (tonnes per person)*

Country (DMU) t	Agriculture	Transport	Industries
Belgium	0.97	2.48	1.42
Czech Republic	0.81	1.56	1.37
Denmark	1.87	2.41	0.55
Germany	0.80	2.05	1.23
Ireland	4.70	3.06	0.88
Greece	0.88	1.96	1.14
Spain	1.01	2.32	0.78
France	1.59	2.25	0.70
Italy	0.66	2.19	0.66
Luxembourg	1.49	13.33	1.66
Hungary	0.90	1.06	0.61
Netherlands	1.17	2.14	1.02
Austria	0.94	2.81	1.31
Slovenia	1.04	2.13	0.59
Slovak Republic	0.62	0.99	2.01
Finland	1.11	2.58	1.14
Sweden	0.98	2.31	0.76
Norway	0.95	3.11	2.23

Table 4A.3 *Employment by year (workers per active people)*

	2000	2001	2002	2003	2004	2005	2006	2007
Agriculture								
Mean	0.0537	0.0516	0.0493	0.0477	0.0456	0.0444	0.0429	0.0414
Max	0.145	0.137	0.131	0.127	0.109	0.108	0.104	0.100
Min	0.0221	0.0217	0.0211	0.0206	0.0202	0.0196	0.0196	0.0195
Std	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02
Transport								
Mean	0.0657	0.0670	0.0647	0.0639	0.0626	0.0616	0.0613	0.0612
Max	0.105	0.112	0.109	0.121	0.126	0.124	0.127	0.119
Min	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Std	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05
Industries								
Mean	0.172	0.174	0.116	0.172	0.158	0.164	0.159	0.158
Max	0.261	0.269	0.262	0.261	0.263	0.259	0.263	0.261
Min	0.10	0.11	0.11	0.10	0.10	0.10	0.10	0.10
Std	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05

Table 4A.4 *Employment by country (workers per active people)*

Country (DMU) *t*	Agriculture	Transport	Industries
Belgium	0.018	0.063	0.135
Czech Republic	0.039	0.067	0.261
Denmark	0.029	0.063	0.144
Germany	0.021	0.050	0.181
Ireland	0.060	0.059	0.145
Greece	0.120	0.053	0.102
Spain	0.046	0.051	0.151
France	0.032	0.057	0.126
Italy	0.038	0.047	0.195
Luxembourg	0.023	0.115	0.171
Hungary	0.051	0.072	0.218
Netherlands	0.031	0.056	0.113
Austria	0.070	0.062	0.156
Slovenia	0.094	0.053	0.242
Slovak Republic	0.037	0.056	0.196
Finland	0.048	0.067	0.171
Sweden	0.023	0.062	0.163
Norway	0.028	0.081	0.114

Table 4A.5 *Gross added value by year (€ per person)*

	2000	2001	2002	2003	2004	2005	2006	2007
Agriculture								
Mean	468.1	481.8	469.9	460.1	469.9	423.9	415.6	457.3
Max	764.8	752.9	753.1	729.5	733.2	710.6	643.7	876.3
Min	209.2	239.1	234.6	223.8	254.1	208.6	214.2	239.4
Std	191.3	189.1	168.2	178.1	163.4	160.3	137.1	166.8
Transport								
Mean	1590.4	1673.5	1753.5	1796.7	1868.0	1921.8	1982.8	2087.7
Max	4734.6	4880.4	5041.3	5005.8	5251.5	5444.6	5710.3	6181.8
Min	359.2	410.3	479.2	490.6	549.0	582.28	593.9	704.4
Std	1052.4	1081.2	1099.0	1061.4	1097.2	1154.8	1199.7	1253.2
Industries								
Mean	3787.9	3865.1	3975.7	3949.8	4050.3	4154.0	4383.2	4665.6
Max	8110.1	8650.1	9673.4	8904.4	8426.0	8162.5	8348.3	8555.7
Min	988.1	1130.4	1295.8	1342.1	1494.2	1636.0	1707.4	1862.0
Std	1930.1	1939.6	2063.3	1911.6	1807.3	1745.3	1817.5	1906.0

Table 4A.6 *Gross added value by country (€ per person)*

Country (DMU) *t*	Agriculture	Transport	Industries
Belgium	259.1	2023.1	4336.1
Czech Republic	244.4	846.2	2079.2
Denmark	540.5	2545.9	4650.6
Germany	253.1	1376.8	5531.1
Ireland	667.4	1709.9	8603.8
Greece	671.7	1282.6	1476.1
Spain	585.4	1253.8	2903.9
France	562.9	1503.2	3309.6
Italy	486.1	1597.5	4096.1
Luxembourg	295.3	5281.3	5421.0
Hungary	292.3	521.1	1460.9
Netherlands	600.4	1943.3	3867.6
Austria	476.1	1768.8	5144.0
Slovenia	313.3	837.6	2815.3
Slovak Republic	301.0	666.6	1772.4
Finland	742.8	2280.4	6245.4
Sweden	499.1	2154.2	5724.9
Norway	413.7	3424.9	4433.0

Table 4A.7 *Energy by year (toe per person)*

Country (DMU) *t*	Agriculture	Transport	Industries
Belgium	0.069	0.940	1.39
Czech Republic	0.057	0.540	0.95
Denmark	0.168	0.940	0.54
Germany	0.029	0.772	0.71
Ireland	0.077	1.146	0.61
Greece	0.104	0.715	0.39
Spain	0.067	0.887	0.67
France	0.060	0.824	0.60
Italy	0.058	0.766	0.70
Luxembourg	0.039	5.20	2.08
Hungary	0.058	0.388	0.34
Netherlands	0.252	0.919	0.90
Austria	0.071	1.01	0.96
Slovenia	0.030	0.72	0.75
Slovak Republic	0.030	0.314	0.79
Finland	0.015	0.910	2.38
Sweden	0.087	0.927	1.46
Norway	0.167	1.04	1.42

Table 4A.8 *Energy by country (toe per person)*

Country (DMU) *t*	Agriculture	Transport	Industries
Belgium	0.069	0.940	1.39
Czech Republic	0.057	0.540	0.95
Denmark	0.168	0.940	0.54
Germany	0.029	0.772	0.71
Ireland	0.077	1.146	0.61
Greece	0.104	0.715	0.39
Spain	0.067	0.887	0.67
France	0.060	0.824	0.60
Italy	0.058	0.766	0.70
Luxembourg	0.039	5.20	2.08
Hungary	0.058	0.388	0.34
Netherlands	0.252	0.919	0.90
Austria	0.071	1.01	0.96
Slovenia	0.030	0.72	0.75
Slovak Republic	0.030	0.314	0.79
Finland	0.015	0.910	2.38
Sweden	0.087	0.927	1.46
Norway	0.167	1.04	1.42

Table 4A.9 *Capital by year (€ per person)*

	2000	2001	2002	2003	2004	2005	2006	2007
Agriculture								
Mean	138	141	148	152	153	163	178	201
Max	260	293	281	329	303	319	422	456
Min	47	59	67	46	58	63	55	73
Std	72	72	73	82	78	82	101	114
Transport								
Mean	664	693	683	640	726	760	748	872
Max	1841	2300	2217	1528	2076	2201	1868	2622
Min	163	147	160	154	185	233	227	249
Std	412	482	469	331	436	465	400	572
Industries								
Mean	643	692	674	660	648	685	717	803
Max	1055	1047	1250	1220	1042	1177	1440	1801
Min	242	240	177	176	221	271	206	266
Std	245	243	259	219	206	221	270	325

Table 4A.10 *Capital by country (€ per person)*

Country (DMU) *t*	Agriculture	Transport	Industries
Belgium	76	729	790
Czech Republic	62	412	2501
Denmark	302	1106	1402
Germany	78	410	739
Ireland	192	1293	708
Greece	145	605	225
Spain	86	654	553
France	164	361	500
Italy	188	606	1035
Luxembourg	307	2082	1211
Hungary	71	190	180
Netherlands	209	542	513
Austria	220	796	782
Slovenia	103	506	673
Slovak Republic	66	351	630
Finland	278	643	772
Sweden	161	783	1910
Norway	161	957	1010